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Comparative Study of Fraudulent Activities and Various Fraud Detection Techniques

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Abstract: *This study highlights the critical role that effective fraud detection systems play by examining the rising occurrence of fraud across industries, which is being driven by technological advancements. By examining a number of fraud categories, such as money laundering, cryptocurrency-related schemes, credit card fraud, and mortgage fraud, this study highlights the need for rigorous preventive measures. By carefully examining a wide range of detection techniques, including Support Vector Machines, Fuzzy Logic, Artificial Neural Networks, Hidden Markov Models, K-Nearest Neighbour, and Bayesian Networks, the research reveals the expanding toolset against fraudulent activity. Through a rigorous examination of applicable literature, creative cutting-edge methods, and astute investigations, the research highlights the crucial necessity of fraud detection systems across a variety of industries. The need for more innovation and interdisciplinary collaboration is highlighted by the discovery of knowledge gaps in real-time data analysis, handling unbalanced datasets, and resilient tactics against adversarial attacks. Our research also contributes to the development of strategies for preventing fraud, ensuring the dependability of financial institutions, and fostering confidence in a time of complex technological connections.*

Keywords: *Fraud, Fraud detection systems (FDSs), S.V.M, A.N.N, H.M.M, Insurance fraud, Credit card fraud, Financial fraud*

I. INTRODUCTION

The Association of Certified Fraud Examiners (ACFE) defines fraud as the intentional theft or exploitation of an organization's resources for one's own financial gain. A variety of industries, including telecommunication networks, mobile communications, online banking, and e-commerce, have seen an increase in fraud incidents as a result of the quick adoption of technology in our daily lives. The rise in fraudulent activities brought on by technology innovation and enhanced worldwide connectivity has resulted in huge financial losses for organizations. As a result, fraud detection is now of the utmost importance.

Fraud detection involves quickly seeing suspicious behaviour as soon as it takes place. Fraud detection tools must improve in order to keep up with crooks who frequently change their tactics. However, the dearth of discussion in this field limits the development of new techniques. Progress is hampered by the frequent lack of public sharing of data sets. Sifting through vast datasets, including log data and records of user behaviour, is necessary to find fraud scenarios. Currently, a variety of techniques are used to spot fraud, including data mining, statistics, and artificial intelligence. Fraud indicators are looked for in data anomalies and patterns. Several types of fraud are covered in this essay, including credit card fraud, telephone fraud, and computer penetration. Online and offline credit card fraud can be distinguished from one another. [1] The use of physically stolen cards at actual stores or call centres is known as offline fraud. The card's issuer can typically stop fraudulent use by proactively locking the card. Contrarily, online fraud occurs when a cardholder is not physically present, such as when making purchases over the phone or the internet. Such transactions do not require handwritten signatures or card imprints, only card data.

Computer incursions are unauthorized attempts to access or change data, and they can make a system unstable. Invasion instances include both external hackers and internal users who are knowledgeable with the system's architecture and security protocols. Misuse intrusions, which make use of known weaknesses, can be further divided into this category, as can anomaly intrusions, which entail aberrations from typical system usage patterns. Network providers lose a lot of money due to telecom fraud because of missed revenue and resource waste. Overlay fraud and subscription fraud are two instances of telecommunications fraud. The former requires using a fictional name to receive services with no intention of paying, whilst the latter involves using illicit services that are discovered through unusual calls on bills. In a larger sense, fraud detection's key objective is to keep forecast accuracy at a tolerable level while reducing forecast error. This involves reducing undiscovered fraud and erroneous alerts. [8] The false alarm rate, fraud detection rate, and false negative rate are significant performance measures. By measuring variables like detection rate, false alarm rate, and average detection time, fraud detection systems try to improve accuracy and reduce false alerts.

II. RELATED WORK

Due to the significance of fraud detection systems in delicate and significant industries, extensive study has been conducted through surveys and review studies. These inquiries cover a wide range of subjects, including fraud domains, types, detection methods, and tactics. Several well-known researchers, including Bolton and Hand (2002), [14] Kou et al. (2004), Phua et al. (2005), Allan et al. (2010), and Pejic-Bach (2010), conducted in-depth investigations on fraud detection using data mining and statistical techniques. Behdad et al. (2012) examined fraud detection techniques that take their cues from organic systems.

This group of artificial intelligence techniques, such as neural networks, mimic biological processes to speed up learning and recognition. They also examined the challenges that fraud detection systems encounter. Li et al. (2008), Travaille et al. (2011), and Liu and Vasarhelyi (2013) have all examined statistical methods for identifying health care fraud. Delamaire et al. (2009) focused on a variety of credit card fraud schemes and the corresponding countermeasures, including pairwise matching, decision trees, clustering, neural networks, and evolutionary algorithms. [3] While Raj et al. (2011) looked at techniques for credit card fraud detection, Rebahi et al. (2011) evaluated VoIP fraud detection systems and classified them as rule-based supervised and unsupervised approaches.

Richhariya (2012), Ngai et al. (2011), and Wang (2010) investigated data mining techniques for detecting financial fraud. [3] A thorough review of the numerous data mining techniques employed as well as the many kinds of medical and vehicle insurance fraud was undertaken by Lookman Sithic and Balasubramanian in 2013.

There are a lot of polls out there, but most of them neglect the challenges that fraud detection systems face. This survey seeks to remedy that by presenting a structured assessment of fraud detection studies. [8] Credit cards, telecommunications, health insurance, auto insurance, and internet auctions are the five industries it covers. It also covers fraud types, detection methods, tactics, barriers, and problems. This survey aims to advance knowledge of existing fraud detection research fields by revealing important barriers to creating effective fraud detection systems.

III. RESEARCH GAP

Numerous research gaps in fraud detection should be looked at in order to increase the effectiveness of detection technologies. A conspicuous area of need is the development of adversarial attack-resistant fraud detection methods. Systems for detecting fraud are using machine learning models more and more, but their susceptibility to manipulation raises concerns about how trustworthy they actually are.

Research on creating more resilient models that can withstand adversarial attempts to fool or manipulate the system could help to ensure the security and integrity of fraud detection systems. Real-time data analysis has also brought to light a research gap that needs to be filled.

[5] The expanding volume and pace of data need real-time or streaming solutions, even though many fraud detection systems are batch processing optimized. By developing algorithms that can recognize fraud patterns as they emerge in dynamic data streams, it is possible to significantly increase the timeliness and accuracy of fraud detection systems. The challenge of handling uneven datasets continues to be a significant issue.

Genuine fraud instances are usually more infrequent than lawful transactions in the field of fraud detection, which causes uneven class distributions. Effective fraud detection requires models that can learn from this skewed data while avoiding biases and false positives. To close this gap and make detection algorithms' predictions fair and accurate, creative ways to decrease the consequences of class imbalance may be required.

IV. TYPES OF FRAUD

Fraudulent activity varies across several industry areas. Numerous studies have identified numerous unique types of financial fraud, including bank fraud, insurance fraud, money laundering, financial statement fraud, mortgage fraud, and healthcare fraud. However, the focus of this essay is on cryptocurrency fraud.

Despite this attention, credit card fraud is still a widespread form of fraud because of how commonly used credit cards are. As a result, researching studies in the financial sector may yield data pertinent to the objectives of this research. So, from 2009 to 2019, the financial industry's methodologies and research were examined in the section that follows. Figure 1 provides a graphic representation of the main types of financial fraud.

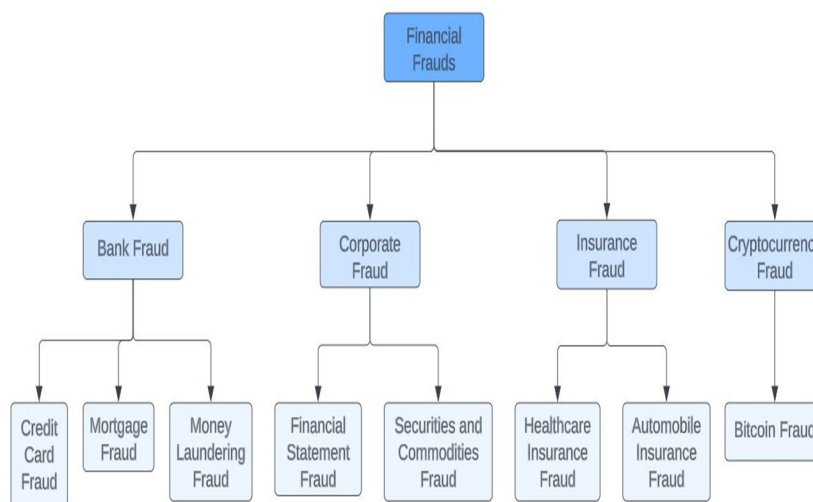


Fig 1: Types of fraud [6]

A. Credit Card Fraud

Credit is a term used to describe the idea of conducting electronic money transactions without using actual money. This concept is embodied by a credit card, a thin piece of plastic that contains customer information and credit services. It has emerged as a key aspect of e-banking and is frequently used for online payments and e-commerce. However, the significant increase in credit card use has also seen an increase in fraud of all kinds. Fraudsters use credit cards for illegal transactions, which costs banks and cardholders a lot of money. Additionally, the creation of fake cards has made fraudulent actions easier to carry out. In order to detect credit card fraud, suspicious transactions are divided into two categories: genuine and fraudulent or suspicious transactions. All measures taken by those who successfully and legally carry out transactions without taking any deceptive steps are considered legitimate transactions. Contrarily, unauthorized or irregular access to the system by individuals results in counterfeit or suspicious transactions, which commonly cause problems. Unlawful credit card fraud is the use of a credit card without the owner's consent. In such cases, the legitimate cardholder is unaware that fraudsters are using their card without their permission. As a result, scammers may access a user's account without authorization or carry out fraudulent operations. Online and offline fraud are the two main types of credit card fraud. Fraudsters that engage in online fraud perform transactions, notably online purchases, using web browsers, cell phones, or the Internet. Offline fraud is when criminals use a stolen credit card to make purchases as if they were the authorized user.

B. Mortgage Fraud

The deliberate misrepresentation and manipulation of mortgage transactions for one's own gain or profit is known as mortgage fraud. This kind of fraud can occur when a loan application or property purchase is being made and can take many different shapes. People may purposefully inflate property valuations, submit false information about their income and employment, and/or misrepresent their intention to occupy a property in order to qualify for larger loans. Other tactics include utilizing straw buyers with excellent credit to obtain loans for buyers with poor credit, engaging in property flipping schemes to inflate property values, and concealing secondary loans received for down payments. Mortgage fraud involves serious financial losses and legal repercussions for lenders, borrowers, and the stability of the housing market. Lenders implement rigorous verification processes and fraud detection technologies to stop these fraudulent methods.

C. Money Laundering

Money laundering is a strategy used by criminals to hide or deceive the source of money that has been gained unlawfully, thereby converting it into legitimate assets. By "cleaning" and "legitimizing" stolen money, fraudsters can successfully conceal its tainted origins.

It involves the purposeful exchange of financial transactions for revenue obtained illegally in order to hide the true source of the money or the nature of the gains. By depicting the funds as having been received legally, this purposeful obscurity aims to provide the impression that they are legitimate. Society as a whole suffers from money laundering. Money laundering worsens criminal behaviour by feeding a vicious cycle, in addition to its immediate repercussions. Criminals and organized groups deliberately blur the line between legitimate and unlawful financial activities. Investigations into illegal activity are hampered as a result, and criminals are given the chance to continue their illegal activities by reinvesting the "cleaned" monies back into their enterprises. In addition, a lot of other criminal activities, including the funding of terrorism and the illicit trade in weapons, depend on money laundering. The stability and security of the entire world are gravely endangered by this complex network of criminality, which not only poses a threat to financial systems. Efforts to stop money laundering are essential to dismantling these complex networks and safeguarding the legitimacy of financial systems and society at large.

D. Financial Statement Fraud

Business financial statements are in-depth records that detail their current financial condition and previous financial activity. Loans, income, expenses, and profits are just a few of the financial details that are included in these accounts. They also offer managerial analysis to describe the success of the business and foresee potential issues in the future. These financial records are necessary for determining the health and viability of an organization as well as for gauging its general success and bankability.

These financial records provide a thorough picture of the organization's state and serve as the foundation for the financial statements of the organization. This data is helpful in determining the organization's level of achievement and financial capability. Sadly, there are instances of financial statement fraud where data is changed to create the appearance of being more favourable than it actually is. [19] This involves rectifying incorrect claims in order to make the organization appear more favourable than it actually is. These fraudulent activities are driven by a number of sources with a range of objectives. These can entail inflating stock prices, obtaining personal bank loans using false information, reducing tax liabilities using false information, or enticing as many investors as possible with an exaggerated picture of financial security. Financial statement fraud compromises financial data and deceives stakeholders who depend on accurate reporting to make informed decisions. Such fraudulent activities need to be addressed if financial reporting systems are to continue to be open, reliable, and reputable.

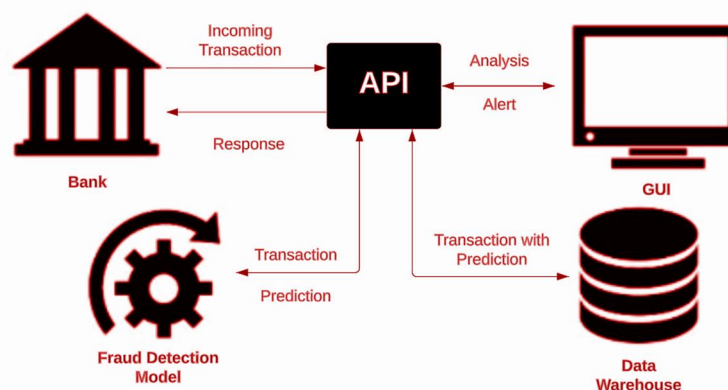


Fig 2 : Fraud detection API for banking related frauds [3]

E. Insurance Fraud

Insurance fraud is the intentional commission of an illegal act with the goal of using insurance coverage to defraud insurance companies of their money. By minimizing potential financial losses, insurance's primary objective is to safeguard the financial interests of both individuals and organizations. A range of stakeholders, including agents and policyholders, might be involved in incidents of insurance fraud, which can occur at any point during the insurance process. This kind of fraud occurs when someone fabricates loss-related assets or creates an unintentional accident to inflate repair and injury costs for unjust financial gain. Insurance fraud affects a variety of sectors relating to insurance, including healthcare, crop protection, automotive coverage, and more. Offenders may fabricate paperwork with inflated expenditures that is allegedly tied to a staged motor accident in cases involving auto insurance claims. In the context of healthcare insurance, dishonest individuals may make false claims claiming fictitious medical services in an effort to fraudulently collect compensation for exorbitantly priced operations or treatments.

Additionally, fraudulent activities are not unheard of in the crop insurance industry, where bad actors manipulate losses related to variations in agricultural prices or unforeseen natural calamities. Such dishonest activities inside the insurance sector not only have a detrimental financial effect, but they also jeopardize the fundamental trust that underpins insurance transactions. [22]A thorough investigation and all-encompassing countermeasures are needed to recognize, thwart, and minimize insurance fraud because of the substantial consequences associated with this crime. Investigating the nuances and variations of insurance fraud across multiple insurance domains is crucial in order to create targeted strategies that uphold the integrity of insurance systems and foster a culture of openness and responsibility.

F. Cryptocurrency Fraud

The term "cryptocurrency fraud" refers to a specific kind of fraud that is intended to trick unsuspecting individuals by promising bogus investment possibilities or services. These dishonest services target those who are less informed on purpose, luring them in with the promise of substantial financial rewards for taking part in such endeavours. Consequently, because they are not aware of the complexity of online investing, many consumers fall for these schemes, particularly those that resemble Ponzi schemes. Understanding that malicious actors utilize bitcoin as a tool to conduct illicit behaviours, such as theft and unauthorized usage of digital currencies, is vital. This is due to the intrinsic decentralization and lax regulation of cryptocurrencies. In this situation, fraudulent services within the bitcoin industry are not created by chance but rather with the purpose of scamming credulous individuals. These cunningly misleading methods entice a number of unwitting victims, yielding huge gains, frequently in the millions of dollars. Vasek and Moore's analysis indicates that there are multiple instances of cryptocurrency investors earning substantial profits, such as btcQuick, Coin Opened, Ubitex, and BTC Promo. Notably, these projects—which are regarded as frauds—were able to bring in an estimated \$11 million. The unique appeal of cryptocurrencies and its decentralized architecture can unintentionally facilitate the proliferation of scams, underscoring the urgent need for strong defences and enhanced public awareness. In order to create effective preventive measures that shield prospective investors from falling for such malicious scams, it is essential to understand the sophisticated strategies fraudsters utilize in the cryptocurrency arena. By carefully scrutinizing the tactics and patterns employed by these fraudulent businesses, researchers and stakeholders can actively work to increase the reliability and integrity of the bitcoin ecosystem.

V. FRAUD PREVENTION TECHNIQUES

Fraud prevention techniques serve as the frontline defences against deceptive practices that can wreak havoc on financial systems, businesses, and individuals. These techniques encompass a variety of strategies, technologies, and methodologies designed to identify, mitigate, and deter fraudulent activities. In an era where financial and digital landscapes are increasingly interconnected, the adoption of robust fraud prevention measures has become imperative to safeguarding assets, data, and the trust of stakeholders.

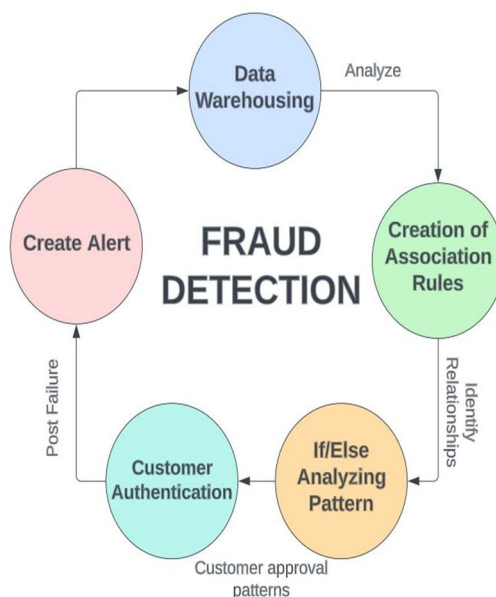


Fig 3 : Process for fraud detection

A. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a linear classification algorithm that builds a decision plane, or hyperplane. Training sets are divided up into many categories by it. SVM has demonstrated potential in identifying fraudulent transactions in a number of research. For instance, Xu and Liu improved an SVM model that outperformed a hybrid ID3+BP model for detecting online credit card fraud. The hybrid SVM-Danger Theory model proposed by Rajak and Mathai performed well in F-Measures and Time Complexity. Using bagging ensemble classifiers, Zareapoor and Shamsolmoali assessed advanced algorithms KNN, NB, and SVM, emphasizing SVM's effectiveness. SVM, linear regression, and logic regression were integrated by Gyamfi and Abdulai for precise legal/illegal behaviour detection in credit card transactions. Hybrid SVM was used by Mareeswari and Gunasekaran to detect credit card fraud. Using One-Class SVM, Sundarkumar et al.[5] improved insurance fraud detection. Francis et al. used SVM to identify fraudulent medical insurance claim submissions. There are issues, such as skewed training data and a dearth of transactions that have been recognized as fraud. To detect credit card fraud, Jeragh and AlSulaimi used an OSVM-autoencoder combination. SVM was effectively utilized by Deng to expose false financial statements, correlating with earlier findings.

B. Fuzzy Logic Based System

Fuzzy logic (FL) is an effective method for dealing with data representation issues in circumstances marked by ambiguity and imprecision. Because of this, FL excels at handling complex modeling scenarios and almost logical reasoning. Behera and Panigrahi suggested a hybrid approach using fuzzy c-means clustering and neural networks for credit card fraud detection in order to decrease false alarms.

HaratiNik et al. developed FUZZGY, a hybrid model combining fuzzy and Fogg behavioural models that performed better, to identify suspicious behaviour in credit card transactions. Nezhad and Shahriari used fuzzy logic and neural-fuzzy Takagi-Sugeno [10] training to increase the accuracy of fraud detection, with a focus on bank systems and cash card services. Supraja and Saritha employed fuzzy logic to build rules for fraud detection in large datasets, showcasing its great performance and accurate detection abilities. Since FL offers accuracy and adaptability to various domains, it is a useful tool for resolving the difficulties of fraud detection.

C. Artificial Neural Network (ANN)

Artificial neural networks (ANN), which are reminiscent of human brain processes, are good at handling massive datasets. Layers of computation are created by organizing the neurons that make up neural networks [14]. Srivastava et al. [17] proposed a fraud detection methodology leveraging a neural network that connects payment gateways with merchants in order to more precisely identify fraudulent transactions.

Ghobadi and Rohani used Cost-Sensitive Neural Networks and the Meta Cost technique to handle skewed data to construct a hybrid fraud detection model. Their method reduced false negatives and raised detection rates. Randhawa et al.'s [15] study of credit card fraud detection using 12 machine learning algorithms addresses privacy concerns.

They employed a range of methods, including hybrid strategies, AdaBoost, SVM, NB, deep learning models, and hybrid models. Using LR and ANN, Sahin and Duman [23] increased the security of credit card transactions. According to their research, ANN outperforms LR at fraud detection. El Bouchti, Chakroun, and colleagues [18] explored Deep Reinforcement Learning (DRL) for banking fraud detection and emphasized its competitive performance and new approach. Data mining techniques used by Ravisankar et al. [21] on a dataset of Chinese businesses predicted financial statement fraud.

D. Hidden Markov Models (HMMs)

Hidden Markov Models (HMMs), which expand on conventional Markov models by including observable state-dependent outputs and unobservable states, are effective tools for complex random processes. HMMs have been utilized to enhance detection techniques in the fight against credit card fraud.

Agrawal et al. proposed a model combining HMM, behaviour-based techniques, and genetic algorithms to identify fraud. Khan et al. increased system simplicity by separating honest from dishonest patterns using HMM. Mhamane and Lobo developed a system using HMM to spot suspicious behaviour in online bank fraud. Wang et al. utilized HMM and K-means to find online payment fraud. Bhusari and Patil took on post-transaction fraud detection using HMM, which resulted in fewer false alarms. Iyer et al. aimed to improve credit card fraud detection accuracy by integrating HMM with K-means clustering. Collectively, these studies show how effective HMMs may be in strengthening credit card fraud detection systems.

E. K-Nearest Neighbour (KNN)

The K-Nearest Neighbour (KNN) algorithm finds nearby neighbours based on similarities in a dataset, often employing Euclidean distance. It serves as a non-parametric classification and regression tool. KNN was successfully employed by Malini and Pushpa to detect credit card fraud via outlier detection. Heryadi et al. outperformed earlier Hidden Markov Model-based results by combining Chi-Square Automatic Interaction Detection with KNN to improve fraud recognition for debit card transactions. A Nearest Neighbours-based approach to auto insurance fraud detection was proposed by Badriyah et al. by merging methods from density-based, distance-based, and interquartile range methodologies. [8] By using feature selection approaches, this method demonstrated how detection accuracy might be improved. In a comparison study of machine learning models for credit card fraud detection, Awoyemi et al. employed KNN to spot fraudulent activity in a European cardholder dataset of 284,807 transactions. KNN performed better than Logistic Regression and Naive Bayes.

F. Bayesian Networks (BN)

Bayesian Networks (BN) represent conditional dependencies between variables using nodes and edges in a directed graph. Deng improved fraud detection accuracy by using a Naive Bayes (NB) classifier for financial statements. Herland et al. modified Multinomial Naive Bayes to identify medical specializations with a 67% success rate after Bauder et al. used it to predict physician anomalies. [7] Hajek and Henriques advocated Bayesian hybrid classifiers in their thorough methodology for the best fraud classification.

G. Decision Trees (DT)

Decision Trees (DT) are tools for classification or regression that use inner nodes to branch to direct binary judgments based on attributes and relationships. Kho and Vea compared a number of classifiers, including NB, Bayes-Net, J48, RT, libSVM, and MOLEM, for the analysis of credit card transaction behavior; Random Tree (RT) demonstrated the greatest accuracy at 94.32%. Devi and Kavitha discovered that DT outperformed SVM and RF in accurately classifying credit card transactions as normal or suspicious. Roy and George utilized DT, RF, and NB, with DT and RF performing best, to find vehicle insurance fraud. In order to detect automobile insurance fraud in the presence of unbalanced data, Subudhi and Panigrahi [4] developed an adaptive oversampling strategy, achieving a high rate of fraud detection using SVM and Decision Tree classifiers.

Table 1 : Comparative analysis of algorithms [6]

FRAUD TYPE	ALGORITHM USED	RESULTS
Credit Card Fraud	S.V.M	A comparison was drawn between the ID3+BP hybrid model and the proposed SVM model, which ultimately demonstrated SVM's superiority. The SVM model showcased an enhancement over the ID3+BP hybrid model, reaffirming its feasibility and effectiveness.
	Fuzzy	Using fuzzy clustering in combination increased detection rate with 93.90% TP and less than 6.10% FP, according to the results.
	HMM	The authors claimed that the suggested approach can be quite helpful in spotting credit card fraud.
	Naïve Bayes	The study's findings demonstrated that Fraud-BNC increased the existing company's economic efficiency by up to 72.64%.
Financial Fraud	S.V.M	The results of the proposed model are consistent with findings from earlier research suggesting that information in issued financial statements is purposefully misrepresented.
	Fuzzy	According to the study's findings, the FGABPN technique has a high

		detection accuracy rating.
	Naïve Bayes	The outcome demonstrated that Bayesian belief networks performed better than other machine learning techniques.
Insurance Fraud	S.V.M	The results raised the accuracy detection rate for identifying insurance claim fraud.
	Fuzzy	The outcome showed that the FL technique reduced time-consuming for large datasets with high dimensionality and obtained good accuracy in detecting insurance claims.
	Naïve Bayes	The findings indicated that this study was useful for a number of disciplines and might categorize doctors who are probably abusing insurance systems.
Cryptocurrency Fraud	S.V.M	The outcomes of our investigation showed promise in terms of prediction accuracy, with SVM achieving an accuracy rate of 86.612% while others had lower accuracy.
	Fuzzy	For identifying fraud in cryptosystems, the authors recommended using neural-fuzzy training.
	Naïve Bayes	The proposed technique was successful in identifying fraud with good results.

VI. FUTURE SCOPE

In the realm of fraud detection techniques, the future holds a spectrum of possibilities. Advancements in AI and machine learning could yield more adaptable models with heightened accuracy, capable of decoding intricate data patterns to enhance detection rates. Transparency gained importance with the rise of AI, prompting the exploration of explainable AI (XAI) methods that shed light on the decision-making process, aiding investigators in understanding flagged cases. Behavioural analytics could elevate detection accuracy by leveraging user behavior patterns and biometrics, while graph analytics and social network analysis might unravel interconnected fraud activities. Continuous adaptive learning could lead to real-time updates of fraud detection models, aligning with evolving fraud tactics. The integration of blockchain could forge transparent and secure transaction records, while IoT devices might bring real-time detection to the edge. Collaboration across industries could yield adaptable strategies, and hybrid models might combine varied fraud detection methods. Ethical considerations and privacy preservation emerge as crucial, balancing accuracy with individual data protection. Regulatory compliance and global cross-border detection could also shape the trajectory of fraud prevention efforts.

VII. CONCLUSION

In conclusion, the surge in fraudulent activities across a range of sectors brought on by technological advancements necessitates a vigilant approach to fraud detection. The complexity of the issue is brought to light by looking at a number of fraud types, including credit card fraud, mortgage fraud, money laundering, and exploding cryptocurrency fraud. A thorough analysis of fraud detection techniques, such as Support Vector Machines, Fuzzy Logic, Artificial Neural Networks, Hidden Markov Models, K-Nearest Neighbour, and Bayesian Networks, reveals a variety of tools for identifying and preventing fraudulent activity in order to counteract this.

The linked work's analysis of the pertinent literature highlights how important fraud detection systems are for safeguarding many firms, encouraging in-depth investigation and algorithmic improvements. Researchers have extensively researched a number of businesses, offering insights into patterns of fraudulent activity and ways to spot it.

Current research gaps include, but are not limited to, the need for adversarial-resistant approaches, real-time data processing, and techniques for handling imbalanced datasets. By accepting innovative solutions and fostering interdisciplinary collaboration, the profession can effectively prevent fraudulent activities, maintaining the stability and credibility of financial institutions in a time of changing technological surroundings.

REFERENCES

- [1] E. Duman, A. Buyukkaya, and I. Elikucuk, "A Novel and Successful Credit Card Fraud Detection System Implemented in a Turkish Bank," 2013 IEEE 13th International Conference on Data Mining Workshops, Dec. 2013
- [2] Yufeng Kou, Chang-Tien Lu, S. Sirwongwattana, and Yo-Ping Huang, "Survey of fraud detection techniques," IEEE International Conference on Networking, Sensing and Control, 2004
- [3] A. Thennakoon, C. Bhagyan, S. Premadasa, S. Mihiranga, and N. Kuruwitaarachchi, "Real-time Credit Card Fraud Detection Using Machine Learning," 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Jan. 2019
- [4] S. Priesterjahn, M. Anderka, T. Klerx, and U. Mönks, "Generalized ATM Fraud Detection," Lecture Notes in Computer Science, pp. 166–181, 2015
- [5] A. Abdallah, M. A. Maarof, and A. Zainal, "Fraud detection system: A survey," Journal of Network and Computer Applications, vol. 68, pp. 90–113, Jun. 2016
- [6] K. G. Al-Hashedi and P. Magalingam, "Financial fraud detection applying data mining techniques: A comprehensive review from 2009 to 2019," Computer Science Review, vol. 40, p. 100402, May 2021
- [7] J. O. Awoyemi, A. O. Adetunmbi, and S. A. Oluwadare, "Credit card fraud detection using machine learning techniques: A comparative analysis," 2017 International Conference on Computing Networking and Informatics (ICCN), Oct. 2017
- [8] R. Sailusha, V. Ganeswar, R. Ramesh, and G. R. Rao, "Credit Card Fraud Detection Using Machine Learning," 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), May 2020
- [9] V. N. Dornadula and S. Geetha, "Credit Card Fraud Detection using Machine Learning Algorithms," Procedia Computer Science, vol. 165, pp. 631–641, 2019
- [10] J. Kim and V. Pavlovic, "A Shape-Based Approach for Salient Object Detection Using Deep Learning," Computer Vision – ECCV 2016, pp. 455–470, 2016
- [11] A. S. Rathore, A. Kumar, D. Tomar, V. Goyal, K. Sarda, and D. Vij, "Credit Card Fraud Detection using Machine Learning," 2021 10th International Conference on System Modeling & Advancement in Research Trends (SMART), Dec. 2021
- [12] D. Rai M. and J. S. N., "Credit Card Fraud Detection using Machine Learning and Data Mining Techniques - a Literature Survey," International Journal of Applied Engineering and Management Letters, pp. 16–35, Jul. 2023
- [13] K. Vengatesan, A. Kumar, S. Yuvraj, V. D. Ambeth Kumar, and S. S. Sabnis, "CREDIT CARD FRAUD DETECTION USING DATA ANALYTICS TECHNIQUES," Advances in Mathematics: Scientific Journal, vol. 9, no. 3, pp. 1177–1188, Jun. 2020
- [14] R. Laimek, N. Kaothanthong, and T. Supnithi, "ATM Fraud Detection Using Outlier Detection," Intelligent Data Engineering and Automated Learning – IDEAL 2018
- [15] S. Doshi, K. Desai, and K. Mehta, "Various Approaches to Object Detection using Deep Learning," International Journal for Research in Applied Science and Engineering Technology, vol. 11, no. 7, pp. 1799–1806, Jul. 2023
- [16] Ngai, E., Hu, Y., Wong, Y., Chen, Y., & Sun, X. (2011, February). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. Decision Support Systems, 50(3), 559–569
- [17] Y. Sahin, E. Duman, Detecting credit card fraud by ANN and logistic regression, in: Innovations in Intelligent Systems and Applications (INISTA), 2011 International Symposium on, IEEE, 2011, pp. 315–319.
- [18] A. Srivastava, M. Yadav, S. Basu, S. Salunkhe, M. Shabad, Credit card fraud detection at merchant side using neural networks, in: Computing for Sustainable Global Development (INDIACom), 2016 3rd International Conference on, IEEE, 2016, pp. 667–670.
- [19] F. Ghobadi, M. Rohani, Cost sensitive modeling of credit card fraud using neural network strategy, in: Signal Processing and Intelligent Systems (ICSPIS), International Conference of, IEEE, 2016, pp. 1–5.
- [20] K. Randhawa, C.K. Loo, M. Seera, C.P. Lim, A.K. Nandi, Credit card fraud detection using adaboost and majority voting, IEEE ACCESS 6 (2018) 14277–14284.
- [21] A. El Bouchti, A. Chakroun, H. Abbar, C. Okar, Fraud detection in banking using deep reinforcement learning, in: 2017 Seventh International Conference on Innovative Computing Technology (INTECH), IEEE, 2017, pp. 58–63.
- [22] P. Ravisankar, V. Ravi, G.R. Rao, I. Bose, Detection of financial statement fraud and feature selection using data mining techniques, Decis. Support Syst. 50 (2011) 491–500.
- [23] Y. Moreau, B. Preneel, P. Burge, J. Shawe-Taylor, C. Stoermann, and C. Cooke. Novel techniques for fraud detection in mobile telecommunication networks. In ACTS Mobile Summit, Grenada, Spain, 1997.



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